A

Topic Approval Seminar Report on

Crop Yield Prophecy with Deep Learning Techniques for Smart Agriculture

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by

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CERTIFICATE

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Abstract

Precision agriculture is an important tool for increasing yields by utilizing natural resources in a diversified setting. Crop output might fluctuate from year to year due to changes in climate, soil characteristics, and fertilizers applied. Automation in the agricultural sector reduces resource consumption and potentially improve food quality in the post-pandemic world. Manual measuring and handling of various portions of crops at various phases of growth is a time-consuming and expensive method for estimating crop yield. The proposed approach attempts to build a model for predicting crop yield using deep learning techniques for smart agriculture that maximizes agricultural productivity. The system will facilitate farmers adopt optimized farming with collaborative deep learning techniques. To increase overall performance, the proposed technique will be evaluated using several measures.

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1. Introduction

Several factors have influenced agriculture's overall health in India. Several innovative technologies have been created to help people regain agriculture's fitness. Precision agriculture is one example of such an approach. Smart agriculture is becoming more popular in India. Precision farming is the revolutionary form of site-specific productivity. It has resulted in more efficient availability and yield, as well as better farming decisions. Precision agriculture has made some advances, but it still has certain challenges. Agricultural experiments in general, as well as crop yield prediction and soil type recommendations, are characterised as difficult agricultural decision-making. This complexity in the subject is largely attributable to the fact that various variables or elements must be considered. Obtaining and utilising historical agriculture data for recommendations is beneficial. Predicting crop yield is difficult since many uncontrollable (elements such as climate, subsidies, demand) and manageable factors (as necessary watering, pest and fertiliser distribution) these all effect crop yield. To predict crop yields based on farmers' long-term experience and the sum of multiple earlier harvests is challenging. The literature discusses the most efficient and potent deep learning techniques for crop yield production. The researchers show that deep learning makes data collection systems for predicting crop yields trustworthy.

In India Wheat takes up more area than any other crop. Wheat is the world's second largest crop in terms of grain acreage and overall production volume. In the marketing year 2021/22, global wheat production totalled approximately 778 million metric tonnes (https://www.statista.com/topics/1668/wheat/#topicOverview). Wheat is the second most important staple food after rice, consumed by 65% (https://vikaspedia.in/agriculture/crop-production/package-of-practices/cereals-and-millets/wheat) of the Indian population, and its consumption is expected to rise further due to changes in eating habits. In our country, wheat is largely consumed in the form of chapati, for which bread wheat occupies approximately 95 percent of harvested land. Durum wheat, which is most suited for creating macaroni, noodles, semolina, and pasta, occupies approximately for 4 to 5% of the area and is primarily farmed in Central and Peninsular India. Predicting wheat crop production is a difficult attempt because it is dependent on a variety of factors like climate, properties of soil, management of crop etc.

2. Literature Review

A prophecy is a prediction, but not just for the weather. Pre denotes "before," and diction is related to speaking. A prediction is thus a guess more about upcoming. It's an interesting observation, usually based on data or facts. Crop production prediction is one of the most difficult challenges in precision agriculture, with several models presented and proven so far. This problem necessitates the use of many datasets because crop output is affected by numerous factors such as climate, weather, soil, fertiliser use, and seed variety [1]. This suggests that crop production prediction is not a simple operation, but rather a series of complex steps. Crop yield prediction methods may now reasonably approximate actual yield, but improved yield prediction performance is still desired [2]. Data mining, machine learning, and deep learning are fields of artificial intelligence that aid in predicting crop productivity based on dataset. The prediction is a two-step process in which the predictive model is built from traits and observations from prior or historical training datasets. In the second stage, the model's performance is assessed using a validating dataset; the training and validation datasets are mutually exclusive.

2.1 Research questions

The goal of this research is to gain a knowledge of deep learning and wheat crop yield prediction. Studies have been examined from several perspectives to get understanding. The four research objectives for this SLR study are listed below.

• What deep learning techniques have been applied in the literature to estimate wheat crop yield?

• What factors have been considered in research to predict wheat crop yield?

• What performance measures have been explored in the literature to predict wheat crop yield?

• What are the challenges in predicting wheat crop yields using deep learning?

2.2 Analysis of referred articles

A clear and concise research process is used, which involves a literature evaluation with regard to wheat crop production prediction utilising deep learning technology as the central objective. The Scopus database is searched for papers with the query (TITLE-ABS-KEY (crop yield) AND TITLE-ABS-KEY (deep learning) AND TITLE-ABS-KEY(wheat)). The phrases are searched in title, abstract or keywords of articles. The search was performed on January 09, 2023. There were a total of 136 research publications detected. After conference papers are excluded, 96 papers are thoroughly reviewed. Given the research in deep learning, it would be difficult to take the literature under all of the applications, thus the search is reduced using the query described previously.

The Journals and Publishers classification indicates where more work in the wheat crop yield prediction with deep learning topic has been published. The most publications are found in Remote Sensing (14.5%), Computers and Electronics in Agriculture (9.3%), Nongye Gongcheng Xuebao Transactions of the Chinese Society of Agricultural Engineering (8.3%), Frontiers in Plant Research (7.2%), and Plant Methodologies (6.25%). Agriculture Switzerland, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, and International Journal of Applied Earth Observation and Geoinformation and Sensors account for 4.16% of total studied articles, while International Journal of Applied Earth Observation and Geoinformation and Sensors account for 3.12%. Each journal has two articles: International Journal of Remote Sensing, Neural Computing and Applications; Neurocomputing, Plants, and Precision Agriculture. Journals with only one research publication are not mentioned due to space constraints. The number of articles published in journals is shown in Table 2.

Table 1 Classification of articles based on journals

Name of Journals	**No. of Articles**
Remote Sensing	14
Computers And Electronics In Agriculture	9
Nongye Gongcheng Xuebao Transactions Of The Chinese Society Of Agricultural Engineering	8
Frontiers In Plant Science	7
Plant Methods	6
Agriculture Switzerland	4
IEEE Journal Of Selected Topics In Applied Earth Observations And Remote Sensing	4
International Journal Of Applied Earth Observation And Geoinformation	3
Sensors	3
International Journal Of Remote Sensing	2
Neural Computing And Applications	2
Neurocomputing	2
Plants	2
Precision Agriculture	2

Considering the publishers, MDPI supplied the most research papers (26%) on wheat crop yield estimates with deep learning algorithms, followed by Elsevier (17%), Chinese Society of Agricultural Engineering (8%), Frontiers Media (7%), BioMed Central Ltd (6%), IEEE (5%), Springer (5%) and Taylor & Francis Ltd (4%). Other publishers contributed a total of 22% to the study. The literature review from the aforementioned publishers reveals a wide range of

research in work. Figure 5 depicts the classification of research articles along with publisher information.

The publication year describes the research direction during the last few years. The graph in Figure 2 depicts wheat crop yield prediction research that began in 2018 and has been steadily improving since then. In 2022, there will be a greater amount of articles published.

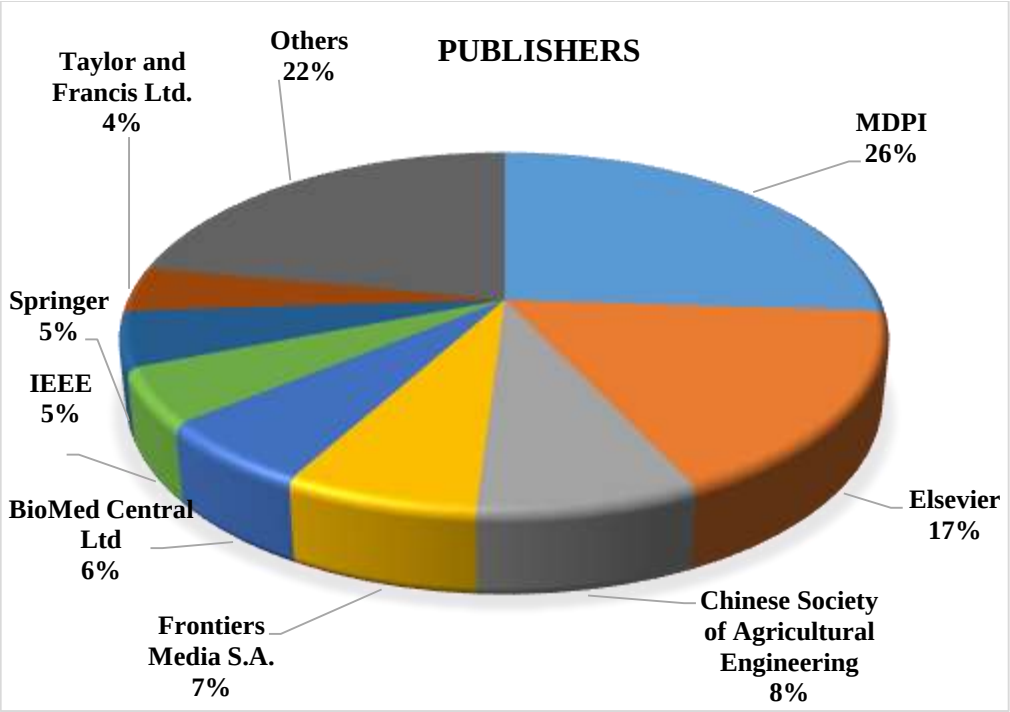

Figure 1 Classification of articles based on publishers

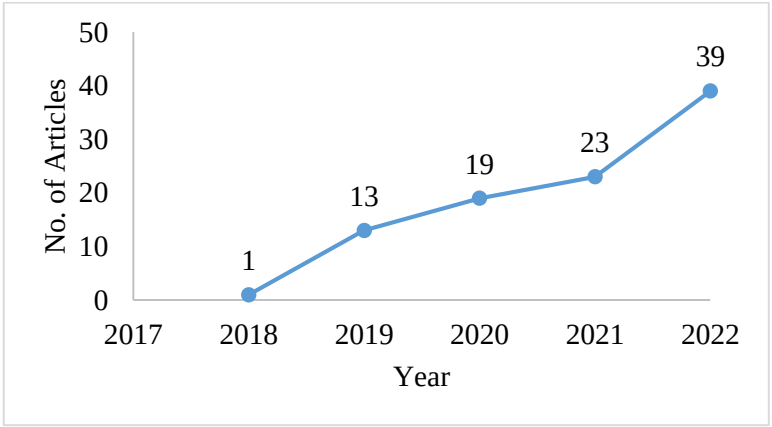

Figure 2 Articles with publication year

2.3 Deep learning algorithms used in crop yield prediction

To achieve the solution goal, many deep learning algorithms for predicting wheat crop yield could be used. Although various algorithms could be utilised, there is no such thing as the optimum algorithm for every situation. Because it is subject to diverse features, a method that is acceptable for solving one problem may not be applicable to another. After an investigation,

few of the deep learning techniques are recognised and illustrated in Figure 3. The following is an explanation of the deep learning algorithms used for predicting wheat crop yield:

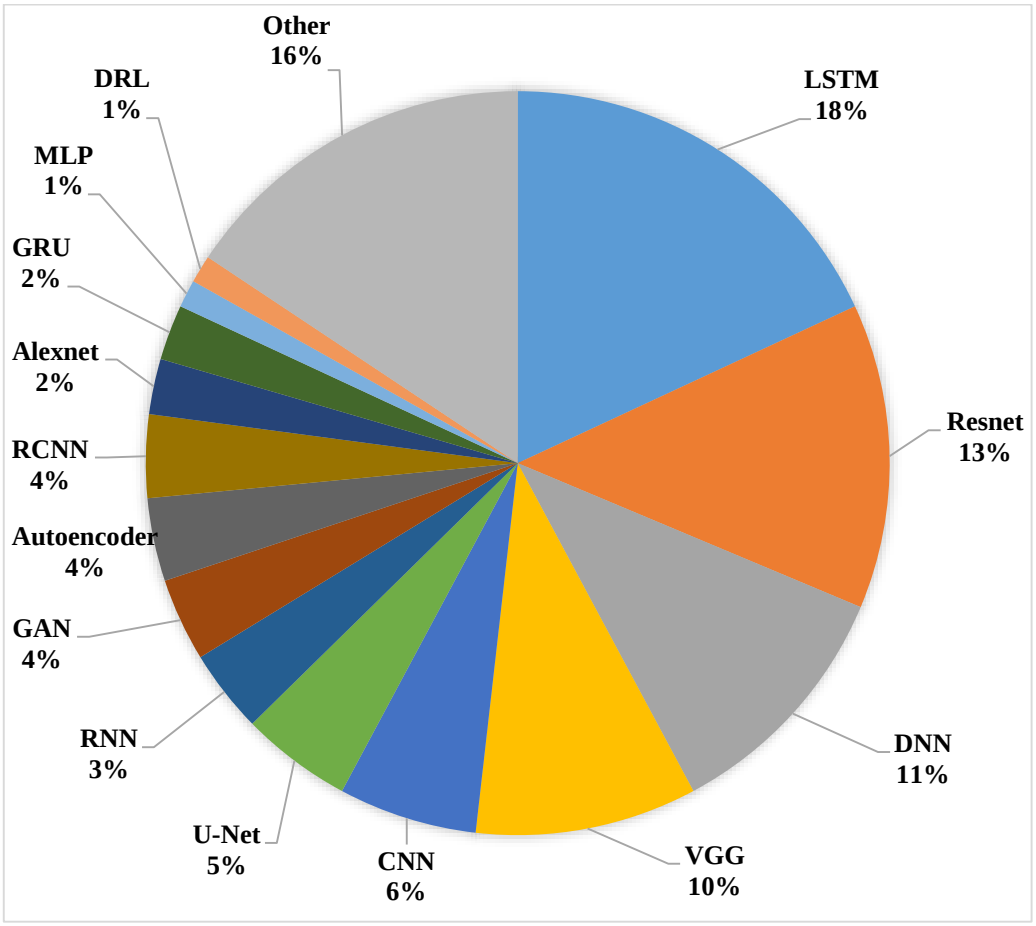

Figure 3 Classification of Deep learning algorithm used in research

Multilayer perceptron

Our brain is made up of many neurons that interact with one another to allow us to do complicated processing and learning as needed. Thus, an artificial model can be created; the most basic artificial model for deep learning is a multilayer perceptron (MLP) known as a feedforward network. The feedforward network maps output to input and learns the parameters that produce the best function optimization. MLP's basic structure comprises of a densely connected network comprising input, output, and several hidden layers. All of these layers are linked together by a dense network of neurons, each with its own weight. [3]. Figure 4 shows the basic MLP with one input, two hidden layers and one output layer.

Convolutional neural network

Convolutional neural network (CNN) is a type of artificial neural network in which the hidden layers are made up of convolutional layers, pooling layers, flatten layers, and fully connected dense layers. CNN continuously conducts the convolution operation together with an input of given width and length in each convolutional layer using kernels and filters. The filter travels

over the input for the same window size, and CNN computes the weighted sum, which creates the feature map. Each of these convolutional procedures learns the coefficient of the "kernel" or filter, which is similar to MLP neurons. [4]. Figure 5 presents fundamental structure of CNN.

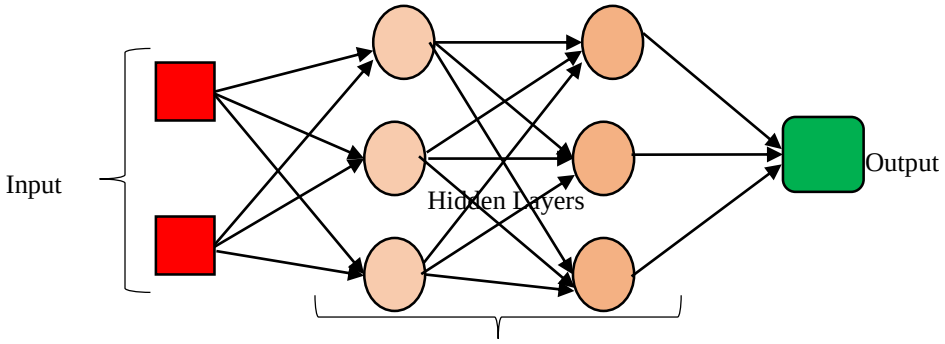

Figure 4 Basic structure of multilayer perceptron

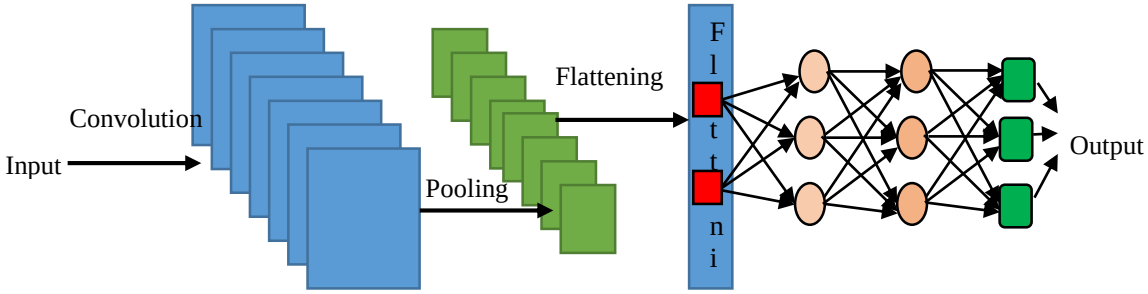

Figure 5 Fundamental structure of CNN

LeNet

LeNet, is a CNN which helps in recognition of digit [5]. A complete convolutional layer is composed of several feature maps, so that multiple features can be extracted at each location. LeNet comprises seven layers shown in Table 2, the input is a 32 x 32-pixel image of characters. The layers and its description is given below in Table 1. Figure 6 taken from [5] shows architecture of LeNet CNN where C_i , S_i, and F_i denotes convolution, subsampling and fully connected layer.

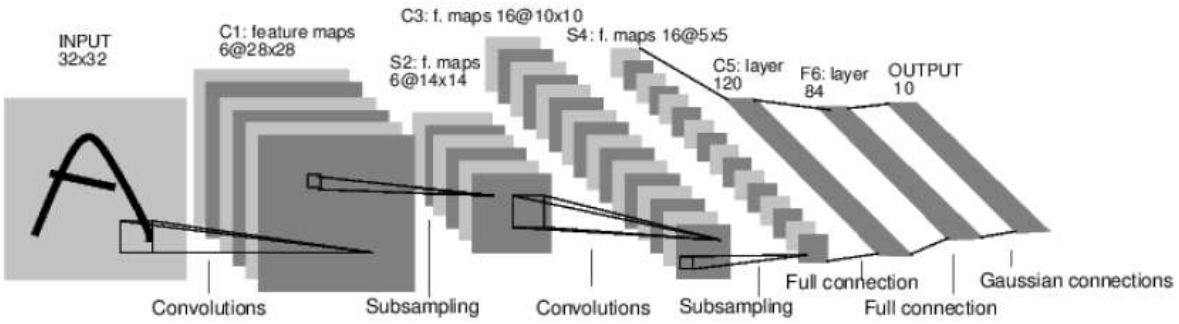

Figure 6 Lenet-5 architecture for recognition of digits

Table 2. Layers in LeNet

Layer	Layer name	Number / Size of feature map	Trainable parameters	Trainable Connections
1	Convolution Layer	6 / 28 x 28	156	122304
2	Subsampling Layer	6 / 14 x 14	12	5880
3	Convolution Layer	16 / 10 X 10	1516	156000
4	Subsampling Layer	16 / 5 X 5	32	2000
5	Convolution Layer	120 /1 x 1		48120
6	Fully connected layer	84 units		10 164
7	Output layer	10 units		

VGGNet

Convolution neural network is referred to as VGGNet used for largescale image recognition, and it was created by the Visual Geometry Group at the Department of Engineering Science, University of Oxford (Karen Simonyan and Zisserman, 2018). They have measured with hidden layers at a depth of 16–19. In order to capture the idea of left/right, up/down, and centre, an architecture with very small (3 X 3) convolution filters was used.

GoogLeNet

Szegedy et al. developed the network with usability and computing effectiveness as their goals, such that implementation can be used on personal computers, even ones with minimal processing power, especially those with small memory footprints. The network is 22 layers deep when counting only layers with. The network consists of 22 hidden layers. There are around 100 layers employed in the network's creation overall. Rectified linear activation is used in GoogLeNet [6].

GoogLeNet is a popular deep CNN model that has achieved the best classification accuracy with top-5 error rate of 6.67% using transfer learning [7]. The architecture consists of 2 deep convolution layers (Conv), 4 max pooling layers, 9 linearly stacked inception modules, 1 average pooling layer along with Stride (S), Padding (P), and number of class (C) values. Each inception module uses 1 × 1 convolutions to do the dimension reduction before moving to larger 3 × 3 and 5 × 5 convolutions. The accuracy of the classification is indicated by the percentage of weed images that the model correctly predicts which is calculated on testing set [7].

ResNet

ResNet, which is short for Residual Network, introduced by He et al. [8] is a special type of neural network. Generally, in order to solve complex problems, one can stack some additional layers in the DNN resulting in improved performance and accuracy. The idea behind adding

additional layers is that these layers progressively learn more complex features. The direct connection that deep ResNet architecture establishes for dispersing information throughout the network demonstrates its high performance. In addition to the typical convolution layers, ResNet also incorporates skip connections that aid in the network's ability to learn global features. The skip connection is connected to add the input x to the output after the weight layers. By removing connections that are not necessary, the network achieves optimal tuning and can train networks more rapidly. Without using this skip connection, the input ′x′ is multiplied by the weights of the layer followed by adding a bias term and then this term goes through the activation function after which the output is obtained. ResNet solves the problem of vanishing gradient in deep neural networks using skip connection by allowing this alternate shortcut path through which the gradient will flow through.

U-Net

A deep convolution network was developed by Ronneberger et al. for the segmentation of biological images. To create more images for training the model, they use data augmentation. The architecture comprises of a symmetric expanding path that permits exact localisation and a contracting path to capture context. Convolution neural networks often need more images to train the model, however they illustrated that a network may be trained from beginning to end with just a small number of images [9]. The U-Net network's structure contains down- and up-sampling, and the entire network resembles the letter "U". The trained U-net model can be used to rapidly segment the image, automatically acquire the necessary features, execute from beginning to end learning and avoid the effects caused by artificial feature selection, incomplete features and insufficient representativeness that happen with the random forest. [10].

Recurrent neural network (RNN)

A stack of recurrently connected hidden layers is supplied an input vector sequence through weighted connections in order to compute the hidden vector sequences first, and then the output vector sequence. RNN is a neural network with short-term memory capabilities. To parameterize a predictive distribution over potential following inputs, each output vector is needed. Every input sequence begins with a null vector, which has all of its entries set to zero. As a result, the network always outputs a prediction for the following input, which is the first genuine input, with no prior knowledge. Every piece of information flowing either vertically or horizontally through the computing graph will be affected by numerous subsequent weight matrices and nonlinearities, indicating that the network is "deep" in both space and time [11].

RNN are frequently used for applications including speech recognition, language modelling, and the creation of natural language. Figure 7 taken from [11] shows architecture of RNN.

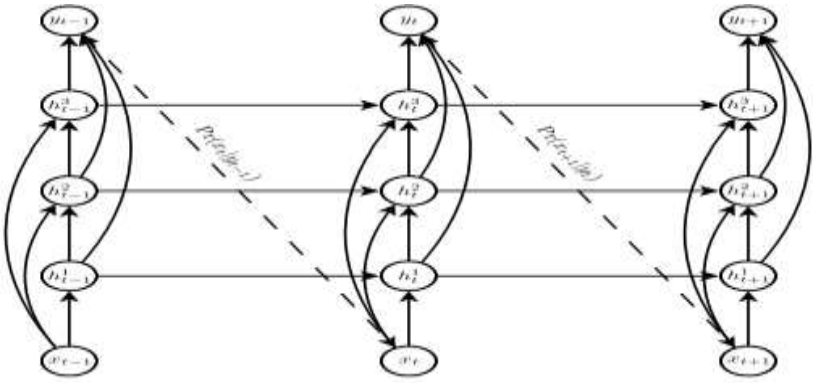

Figure 7. Deep recurrent neural network prediction architecture [11]

LSTM

LSTM is a unique type of RNN, because of its recursive structure, gating mechanism, and processing of sequential data in addition to its control over information input and exit into and out of cells. With outstanding findings, LSTM was employed across many research to estimate crop yield. The LSTM is frequently chosen for classification, processing, and prediction based on time series data since it contaizns feedback connections and can accept input sequences of any length. LSTM not only captures trends in the data but also describes the dependencies of the time series data [12]. In a cyclic neural network, a neuron cannot only receive information from other neurons but also its own information, forming a network structure with loops. Compared with feedforward neural networks, RNN are more in line with the structure of biological neural networks. RNNs are composed of a series of neural network repeating modules. The backpropagation algorithm can gradually learn the parameters of RNN. The error information is transmitted in reverse chronological order using the backpropagation process. Gradient explosion and extinction are issues that arise with reasonably long input sequences. The cyclic neural network has undergone several changes in order to address this issue. Introduction of a gating mechanism, is the most efficient way to improve cyclic neural network. A simple cyclic neural network can experience gradient explosion or even vanish, but the LSTM is a variation of the cyclic neural network that can handle these issues well.

A gating system is employed by the LSTM network to regulate the direction of transmitting data. The LSTM can modify the cell state by removing or adding information, which is carefully controlled via gates. The input gate (i_t), forget gate (f_t), and output gate (o_t) are the three "gates" used in LSTM. ft determines how much data must be forgotten to regulate the internal state c_t-1 at the last moment; i_t determines the candidate status c_t at the moment and how much data must be preserved; The amount of data from the internal state c_t that must

currently be output to the exterior state h_t is controlled by o_t. Cell structure of the LSTM network is shown in Figure 8.

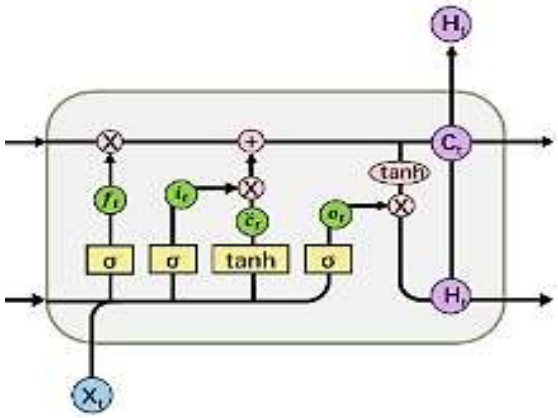

Figure 8 Cell structure of the LSTM network [12]

The beauty of LSTM is that the weight of the self-loop may be modified by raising the input threshold, forgetting threshold, and output threshold. As a result, when the model parameters are fixed, the integration scale at various periods can be altered dynamically, eliminating the issue of gradient expansion or vanishing.

2.4 Wheat crop yield prediction with different factors

The advancements in data science, sensor technology, and machine and deep learning have boosted hopes for farmers to develop more efficient and effective ways to improve production. Several machine learning and deep learning models have already been investigated in numerous domains of agriculture, including crop yield prediction and measuring the impact of various climatic conditions and agricultural methods on overall crop productivity.

Evans and Shen investigated whether phenological and seasonal climate metrics derived from spatially weighted growth curve (SWGC) estimates which used to estimate wheat production on Landsat NDVI. They identified best models by combining phenological and seasonal climatic indicators: multi-layer perceptron (MLP) deep learning and support vector regression models and selected the MLP model as the best because it is faster to implement and yields more in years with a reasonable number of cloud-free images [13]. Di et al. suggested a long- and short-term memory model (BO-LSTM) based on Bayesian optimisation that combines crop phenology, climatic, and remotely sensed information to estimate county level winter wheat yields. When compared to linear regression, machine learning, and deep learning, the BO-LSTM model exhibited the best yield prediction performance with RMSE = 177.84 kg/ha, R^2 = 0.82.[14]. Fei et al. revealed that the ensemble feature selection strategy increased grain yield prediction from hyperspectral data and also assisted wheat breeders in making earlier decisions [15]. The leaf area index serves as input data for the yield predict model. The results

demonstrated that the accuracy of the yield estimation results using LSTM is greater compared to traditional machine learning approaches, with R^2 = 0.87 [12]. Huang et al. used official county-level statistics of past winter wheat yields to train and test the deep learning model. They explored at non-linear connections between winter wheat yield and predictor variables derived from a variety of sources, including remote sensing, weather, and soil parameters [16]. Tripathi et al. predicted wheat yield from remotely sensed data, Sentinel-1 and Sentinel-2 of Punjab, India, by taking parameters like soil moisture, soil salinity, and soil organic carbon into consideration. The soil health-based deep learning MLP model performed better over least squares regressor in crop yield estimation, with R^2 values of 0.723 and 0.684 in the training and testing stages, respectively [17]. The Sentinel-2 images was used to obtain LAI to predict crop yield by Xie. The author discussed combination of crop growth models, remotely sensed, and the LSTM approach to provide more trustworthy crop yield projections across wide areas [18]. Xie and Huang used DL approaches to combine a crop-growth model with time series of remotely sensed data to increase the accuracy of provincial wheat yield predictions in Henan Province, China. The LSTM model generated more good prediction of wheat yields than the 1-D CNN and RF models, having greater R^2 values and smaller root mean square error (RMSE) and mean relative error (MRE) values [19]. Moghimi et al. created a sensor-based system for wheat yield phenotyping. They could successfully predict the yield of test plots with $R^{2=}$0.41 and NRMSE=0.14 along with sub-plots with R^2 =0.79 and NRMSE =0.24 [20]. Nevavuori et al. concentrated on a spatial level that allowed them to estimate intra-field yield distribution in the setting of particular farm crop management. The results show that CNN models may generate reasonably accurate yield predictions based on RGB images. They discovered that the CNN model appeared to do well for RGB images than with NDVI images [21].

Daniel et al. created a system that assisted in crop selection and price prediction in order to improve farmers' crop selection with a high benefit. They used the soil test report to calculate the amount of fertiliser required [22]. Manikandakumar & Karthikeyan used CNN with an effective Particle Swarm Optimization (PSO) technique to improve and increase weed classification accuracy. CNN model is significantly improved the success rate by 97.79% - 98.58% [7]. Colour component selection and image analysis approaches, together with deep learning, were presented to identify and quantify wheat spikelet in colour photographs. CNN successfully estimates the quantity of wheat spikelet, which enhances wheat spikelet counting effectiveness and adds to the understanding of wheat spike development features [23]. Alkhudaydi and De La lglesia developed spike count, a fully convolutional network that uses a density estimation technique to count spikelets [24].

Wheat has been found to be heavily damaged by different diseases because of increasing seasonal variance. Wheat diseases can severely reduce yield and pose a major danger to the world's food supply. Infectious wheat plants frequently exhibit symptoms that skilled agricultural specialists use to diagnose the type of disease ailing the plant. The traditional visual method of diagnosis, on the other hand, is time-consuming and difficult, necessitating highly educated experts who are intrinsically constrained in their ability to cover huge areas. As a result, researchers investigated diseases and used deep learning to automate health diagnosis for wheat plants. Li et al. suggested a viable aphid preventive approach. Experimental findings on dataset utilised with CNN reach aphid counting performance of 10.22 Mean Absolute Error (MAE) and 12.24 Mean Squared Error (MSE) [25]. Nigam et al. proposed a CNN approach for detecting healthier and yellow rust-infected wheat leaves. They achieved a testing accuracy of 97.3% and a training accuracy of 98.42% [26]. J. Jiang et al. used field images to detect wheat leaf disease like powdery mildew, leaf rust, and stripe rust. They developed different deep convolutional neural networks for crop disease diagnosis and achieved the highest identification accuracy of 92.5% on the test dataset with the Inception-v3 CNN model. [27].

Due to population growth and human activity, water shortage has become a major concern. Crop water stress monitoring in real time can help with precision irrigation control and reduce yield loss due to water loss. Chandel et al. discovered that DL models outperformed ML models for stressed and non-stressed crop categorization. DL-LSTM exhibited the best accuracy (96.7%) of the function approximation-based techniques tested. ResNet50 had the highest accuracy of the feature extraction-based techniques, with 96.9% and 98.4% with RGB and thermal imagery inputs, respectively [28]. Jia et al. investigated deep learning and the hybrid fuzzy uncertainty optimisation method to forecast agricultural yield per unit area and a benefit planning model for water management. The integration of the two models, via the crop-water production function, can efficiently deal to crop plantation area and useful precipitation, as well as unpredictable information such as irrigation water allocation costs. [29]. Fei et al. used multispectral data and ensemble learning to build ML including Cubist, support vector machine deep neural network, ridge regression, and random forest (RF) for wheat grain yield prediction. They examined the yield prediction capabilities of low, moderate, and higher watering regimens. The results demonstrated that low altitude unmanned aerial vehicle-based multispectral data may be used to estimate early grain yields with high precision utilising data fusion and an ensemble learning framework. [30]. The author described the agricultural landscaping and optimisation plan and noticed some improvement in water storage for rice, ice, wheat, maize and potatoes [31]

Table 3 Summary of literature review

Authors	Parameter	Data	Techniques Used
[12].	Single-leaf area index (LAI)	MODIS LAI	LSTM
[16]	Temperature, air pressure, specific humidity, wind speed, downward shortwave radiation, downward longwave radiation, and precipitation rate. Clay, silt, sand content, coarse fragments, and bulk density	Remote sensing, weather, and soil properties)	VGG, ResNet, DenseNet, Inception, LSTM, and GRU
[24]	Spike count	RGB image series used in this work, ACID	CNN
[17]	Soil health parameters-Soil Moisture, Soil Salinity, and Soil Organic Carbon (SOC)	sentinel	DLMLP
[18]	the time series of leaf area index (LAI) and yields simulated from CERES-Wheat model, and the LAI retrieved from Sentinel-2 imagery.	Sentinel-2 data	LSTM
[13]	Remotely sensed phenology, climate data, Landsat NDVI	Landsat-7	SVM, MLP

[19]	LAI	LAI and yield during the wheat-growing stages	LSTM, 1-D CNN and RF
[20]	NDVI	images using UAV	MLP
[21]	Climate	UAV images	CNN
[22]	Soil test report, The pH level of the soil	Soil health data, crop production data and rainfall data	SVM: Crop recommendation, Price Prediction: ANN, RNN
[7].	Identification of weed	Weed Images	PSO and CNN
[23].	Spikelet	Colour images	CNN
[24]	Spike count	RGB image series used in this work, ACID	CNN
[25]	Identification of aphid	1100 images of aphids	CNN
[26]	Healthy leaves and yellow rust infected leaves in the wheat crop	2000 images that consist of healthy leaves (1000 images), yellow rust infected leaves (1000 images)	CNN
[27]	Powdery mildew, leaf rust, and stripe rust	Field-based Wheat Diseases Images	Inception-v3 CNN
[28]	Canopy temperature, relative water content, soil moisture content.	Thermal and RGB images (1600 each) were labeled	LSTM

		into stressed and non- stressed	
[29].	Precipitation, Water cost	Daily precipitation of area	LSTM
[30]	Crop height, texture and vegetation index extraction	Images taken by drone	Support vector machine, DNN, ridge regression and random forest
[31]	Landscape	Experimental site	Deep Reinforcement Learning

3. Research Gap

- The majority of research incorporating data from remote sensing.
- Crop yield forecast is taken into account at the national level but not at the farm level.
- Water planning for crop yield is not addressed efficiently.
- Less accuracy is observed for deep learning models.

4. Problem Definition

Traditional agriculture and the linked sector are incapable of meeting the demands of modern agriculture, which demands high-yielding, high-quality, and increased performance. And hence, it is critical to focus on automating existing methods and utilising information technology and data over a certain time period to estimate the maximum possible production and crop appropriate for the specific land. Furthermore, farmers must be aware of the crops that must be planted based on previous years' experiences. The DL algorithm created innovative chances to enhance farmers' judgement and guide operations in a variety of real-world challenges with or without minimum human participation. DL approaches have the ability of tackling large nonlinear problems automatically by combining information from many sources; it also gives a versatile and resilient structure for deciding and introducing expertise into the system based on data. Certain algorithms are not fundamentally reliable, which may result in inaccurate yield predictions when applied to unknown datasets. Thus employing the DL method, great prediction accuracy and computational speed, as well as good consistency across outcomes, must be prioritised. Many machine learning (ML) methods have been utilised throughout the years for crop yield predictions of specific crops in various regions.

Water used for irrigation should be treated differently in agriculture because it accounts for a major share of total water use. Irrigation planning is crucial in agricultural production because it ensures a constant yield while reducing the risk of losing caused by water scarcity. As a result, developing an autonomous watering strategy using modern technology is critical. Deep learning algorithms have received a lot of interest in agriculture and have previously been utilised successfully. Deep learning's major goal is to teach computers how to use data or experience to solve real-world problems. In this study, we will focus on the use of deep learning techniques to solve real-life problems in agriculture. Human inspection is time-consuming, labour intensive, and prone to human mistake; thus, there is an obvious need to develop more effective and efficient watering strategies through the use of automated systems. We propose crop yield prophecy with deep learning techniques for smart agriculture that maximises crop yield

The primary goal of this research will be to develop a farm-scale system for scheduling and optimising water use on the farm while maximising crop yield. This technology will aid in increasing the water value of today's agricultural businesses. An integrated crop and water management system that meets the particular needs of a farm could be a fascinating way to use water in the most efficient and waste-free manner while enhancing crop yield.

5. Objectives

- To design a deep learning model on farm-wide scale for prediction of crop yield with weather and soil nutrients dataset.
- To provide optimized schedule for water management to maximize the crop yield.
- To improve accuracy

6. Proposed Methodology

The proposed crop yield prediction model would employ deep learning method approaches to allow the user to anticipate the yield of crops in advance. The models are trained using historical data containing weather, soil nutrients, and soil characteristics. To prepare the dataset for model building, it will be pre-processed. The dataset will be divided into two parts: training and testing. The training dataset will be used to develop the model to predict the crop yield with watering strategy. On the other side, the testing dataset will be utilised to evaluate the created model; if the accuracy of the evaluated model is satisfactory, it may be used to estimate crop yield with effective crop watering planning. The Figure 9 shows the steps in proposed methodology to predict crop yield.

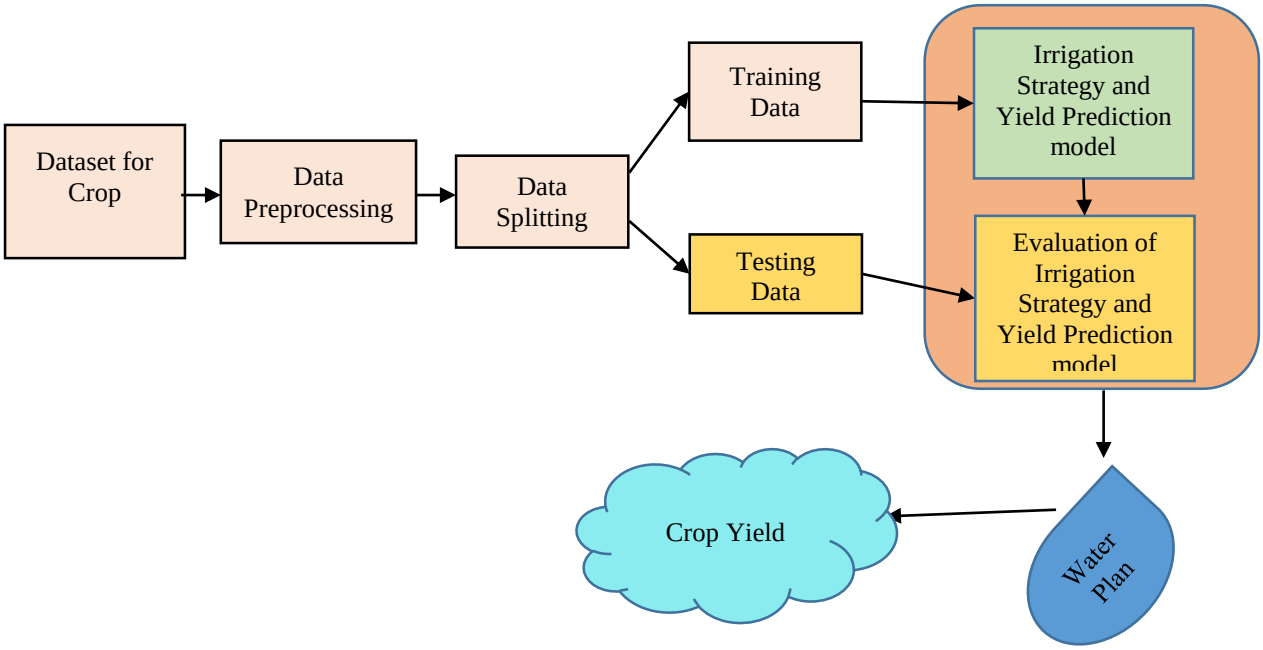

Figure 9 Proposed Methodology Architecture

7. Expected Outcomes

- An integrated crop and water management model that meets the particular needs of a farm.
- Great prediction accuracy and computational speed, as well as good consistency across crop yield outcome
- User friendly system

8. Performance Parameters

Statistical metrics coefficient of determination (R^2), root mean square error (RMSE), mean absolute percentage error, mean absolute error, precision, recall and Kappa coefficient were used to assess the predictive models' robustness. The crop yield prediction depends on more than one independent variable. So the equation to predict crop yield (C_{yld}) can be written as.

$$C_{yld} = w_0 + w_1 v_1 + w_2 v_2 + w_3 v_3 + \cdots + w_n v_n + \beta \quad (1)$$

where C_{yld} is the crop yield that is to be determined, w_0 is the fittest model's *y*-intercept by the, $v_1, v_2, v_3 \ldots v_n$ are the values of the variables that affect yield, stands for error, $w_1, w_2, w_3 \ldots w_n$ are the model coefficients, which are defined as the amounts by which yield changes as a result of changes in the corresponding variables [12].

The crop yield is predicted (P_C_{yld}), once the model has been developed using deep learning techniques. Model is assessed by using statistical metrics, taking into account C_{yld} and P_C_{yld} for *n* observations.

Coefficient of determination (R^2)

R^2 determines the proportion of crop yield variance that can be accounted for by the various factors. Equation (2) represents the mathematical expression for *r*.

$$r = \frac{n\sum_{i=1}^{n} C_{yld_i} * P_{C_{yld_i}} - \sum_{i=1}^{n} C_{yld_i} * \sum_{i=1}^{n} P_{C_{yld_i}}}{\left(\sqrt{n\sum_{i=1}^{n} {C_{yld_i}}^2 - \left(\sum_{i=1}^{n} C_{yld_i}\right)^2}\right) * \left(\sqrt{n\sum_{i=1}^{n} {P_{C_{yld}}}^2 - \left(\sum_{i=1}^{n} P_{C_{yld}}\right)^2}\right)} \quad (2)$$

For understanding statistical correlation using the coefficient of correlation (*r*), Sharma and Singh (Sharma and Singh 2018) provide the following general rules:

- If value of r is between 0.68 to 1 then there is strong correlation between C_{yld} and P_C_{yld}
- If value of r is between 0.36 to 0.67 then there is moderate correlation between C_{yld} and P_C_{yld}
- If value of r less than 0.35 then there is weak correlation between C_{yld} and P_C_{yld}

R^2 which ranges from 0 to 1, is the square of the correlation coefficient (r) [32] expressed in Equation (3).

$$R^2 = (r)^2 \quad (3)$$

The parameters being utilised to predict crop yield are not good if R^2 is close to zero, while the crop yield can be estimated error-free when its value is 1. R^2 is a relative measure of fit.

Root mean square error (RMSE)

RMSE is a unit of measurement for the standard deviation of variations between actual values and predicted values. It is expressed with the square root of the mean of the square of all the errors. It indicates the absolute fit of actual values to the predicted values. A lower RMSE value indicates a more accurate fit and responsiveness of the prediction model [32]. Equation (4) represents the mathematical expression for *RMSE*.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(C_{yld_i} - P_{C_{yld_i}}\right)^2}{n}} \quad (4)$$

Accuracy

In supervised classification, accuracy is the evaluation index that is most frequently used. It consists of the proportion between the total number of samples and the number of samples that

were correctly predicted. The model is more trustworthy when its accuracy is better. Equation (7) can be used to calculate accuracy.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

where true positivity (TP) and True negativity (TN) indicates that the prediction is correct, and both the predicted value and the truth value are matching. False positivity (FP) and False negativity (FN) implies a prediction error means that the prediction is wrong; that is, the predicted value and the truth value does not match.

9. Conclusions

- The proposed system will facilitate farmers adopt optimized farming with collaborative deep learning techniques.
- It will also make it possible to carry out effective watering plan actions to maximize productivity.
- The proposed model will be evaluated using performance parameters to improve the accuracy.

References

[1] X. Xu *et al.*, "Design of an integrated climatic assessment indicator (ICAI) for wheat production: A case study in Jiangsu Province, China," *Ecol. Indic.*, vol. 101, no. April 2018, pp. 943–953, 2019, doi: 10.1016/j.ecolind.2019.01.059.

[2] P. Filippi *et al.*, "An approach to forecast grain crop yield using multi-layered, multi-farm data sets and machine learning," *Precis. Agric.*, vol. 20, no. 5, pp. 1015–1029, 2019, doi: 10.1007/s11119-018-09628-4.

[3] C. Angermueller, T. Pärnamaa, L. Parts, and O. Stegle, "Deep learning for computational biology," *Mol. Syst. Biol.*, vol. 12, no. 7, p. 878, 2016, doi: 10.15252/msb.20156651.

[4] K. S. Sandhu, D. N. Lozada, Z. Zhang, M. O. Pumphrey, and A. H. Carter, "Deep Learning for Predicting Complex Traits in Spring Wheat Breeding Program," *Front. Plant Sci.*, vol. 11, no. January, 2021, doi: 10.3389/fpls.2020.613325.

[5] Y. Lecun, B. Leon, B. Yoshua, and H. Patrick, "Gradient-Based Learning Applied to Document Recognition YANN," *Proc. IEEE*, vol. 86, no. 11, pp. 1299–1305, 1998, doi: 10.1109/5.726791.

[6] C. Szegedy *et al.*, "[googLenet]Going deeper with convolutions Christian," *Popul. Health Manag.*, vol. 18, no. 3, pp. 186–191, 2015, [Online]. Available: http://online.liebertpub.com/doi/10.1089/pop.2014.0089.

[7] M. Manikandakumar and P. Karthikeyan, "Weed Classification Using Particle Swarm Optimization and Deep Learning Models," *Comput. Syst. Sci. Eng.*, vol. 44, no. 1, pp. 913–927, 2022, doi: 10.32604/csse.2023.025434.

[8] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, vol. 2016-Decem, pp. 770–778, 2016, doi: 10.1109/CVPR.2016.90.

[9] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation," *IEEE Access*, vol. 9, pp. 16591–16603, 2021, doi: 10.1109/ACCESS.2021.3053408.

[10] S. Liu *et al.*, "The Accuracy of Winter Wheat Identification at Different Growth Stages Using Remote Sensing," *Remote Sens.*, vol. 14, no. 4, 2022, doi: 10.3390/rs14040893.

[11] A. Graves, "Generating Sequences With Recurrent Neural Networks," pp. 1–43, 2013, [Online]. Available: http://arxiv.org/abs/1308.0850.

[12] J. Wang, H. Si, Z. Gao, and L. Shi, "Winter Wheat Yield Prediction Using an LSTM Model from MODIS LAI Products," *Agriculture*, vol. 12, no. 10, p. 1707, 2022, doi: 10.3390/agriculture12101707.

[13] F. H. Evans and J. Shen, "Long-term hindcasts of wheat yield in fields using remotely sensed phenology, climate data and machine learning," *Remote Sens.*, vol. 13, no. 13, 2021, doi: 10.3390/rs13132435.

[14] Y. Di, M. Gao, F. Feng, Q. Li, and H. Zhang, "A New Framework for Winter Wheat Yield Prediction Integrating Deep Learning and Bayesian Optimization," *Agronomy*, vol. 12, no. 12, pp. 1–15, 2022, doi: 10.3390/agronomy12123194.

[15] S. Fei, L. Li, Z. Han, Z. Chen, and Y. Xiao, "Combining novel feature selection strategy and hyperspectral vegetation indices to predict crop yield," *Plant Methods*, vol. 18, no. 1, pp. 1–13, 2022, doi: 10.1186/s13007-022-00949-0.

[16] H. Huang *et al.*, "Developing a Dual-Stream Deep-Learning Neural Network Model for Improving County-Level Winter Wheat Yield Estimates in China," *Remote Sens.*, vol. 14, no. 20, 2022, doi: 10.3390/rs14205280.

[17] A. Tripathi, R. K. Tiwari, and S. P. Tiwari, “A deep learning multi-layer perceptron and remote sensing approach for soil health based crop yield estimation,” *Int. J. Appl. Earth Obs. Geoinf.*, vol. 113, no. July, p. 102959, 2022, doi: 10.1016/j.jag.2022.102959.

[18] Y. Xie, “Combining CERES-Wheat model, Sentinel-2 data, and deep learning method for winter wheat yield estimation,” *Int. J. Remote Sens.*, vol. 43, no. 2, pp. 630–648, 2022, doi: 10.1080/01431161.2022.2026521.

[19] Y. Xie and J. Huang, “Integration of a crop growth model and deep learning methods to improve satellite-based yield estimation of winter wheat in henan province, china,” *Remote Sens.*, vol. 13, no. 21, 2021, doi: 10.3390/rs13214372.

[20] A. Moghimi, C. Yang, and J. A. Anderson, “Aerial hyperspectral imagery and deep neural networks for high-throughput yield phenotyping in wheat,” *Comput. Electron. Agric.*, vol. 172, no. April, p. 105299, 2020, doi: 10.1016/j.compag.2020.105299.

[21] P. Nevavuori, N. Narra, and T. Lipping, “Crop yield prediction with deep convolutional neural networks,” *Comput. Electron. Agric.*, vol. 163, no. July, p. 104859, 2019, doi: 10.1016/j.compag.2019.104859.

[22] J. Daniel, R. Shyamala, R. Pugalenthi, and P. Mohan Kumar, “RANC-CROP Recommendation Attributed to Soil Nutrients and Stock Analysis Using Machine Learning,” *IETE J. Res.*, 2022, doi: 10.1080/03772063.2022.2060868.

[23] R. Qiu, Y. He, and M. Zhang, “Automatic Detection and Counting of Wheat Spikelet Using Semi-Automatic Labeling and Deep Learning,” *Front. Plant Sci.*, vol. 13, no. May, pp. 1–11, 2022, doi: 10.3389/fpls.2022.872555.

[24] T. Alkhudaydi and B. De La lglesia, “Counting spikelets from infield wheat crop images using fully convolutional networks,” *Neural Comput. Appl.*, vol. 34, no. 20, pp. 17539–17560, 2022, doi: 10.1007/s00521-022-07392-1.

[25] R. Li *et al.*, “A multi-branch convolutional neural network with density map for aphid counting,” *Biosyst. Eng.*, vol. 213, pp. 148–161, 2022, doi: 10.1016/j.biosystemseng.2021.11.020.

[26] S. Nigam *et al.*, “Automating yellow rust disease identification in wheat using artificial intelligence,” *Indian J. Agric. Sci.*, vol. 91, no. 9, pp. 1391–1395, 2021, doi: 10.56093/ijas.v91i9.116097.

[27] J. Jiang *et al.*, “Evaluation of Diverse Convolutional Neural Networks and Training

Strategies for Wheat Leaf Disease Identification with Field-Acquired Photographs," *Remote Sens.*, vol. 14, no. 14, 2022, doi: 10.3390/rs14143446.

[28] N. S. Chandel, Y. A. Rajwade, K. Dubey, A. K. Chandel, A. Subeesh, and M. K. Tiwari, "Water Stress Identification of Winter Wheat Crop with , State-of-the-art A I Techniques and High-Resolution Thermal-RGB Imagery," 2022.

[29] W. Jia, Z. Wei, and L. Zhang, "A Novel Prediction and Planning Model for the Benefit of Irrigation Water Allocation Based on Deep Learning and Uncertain Programming," *Water*, vol. 14, no. 5, 2022, doi: //doi.org/10.3390/w14050689.

[30] S. Fei *et al.*, "UAV-based multi-sensor data fusion and machine learning algorithm for yield prediction in wheat," *Precis. Agric.*, no. 0123456789, 2022, doi: 10.1007/s11119-022-09938-8.

[31] Y. Cui, "Landscaping Agricultural and Animal Husbandry Production Park Using Lightweight Deep Reinforcement Learning under Circular Symbiosis Concept," *Comput. Intell. Neurosci.*, vol. 2022, no. Ml, 2022, doi: 10.1155/2022/8410996.

[32] L. K. Sharma and T. N. Singh, "Regression-based models for the prediction of unconfined compressive strength of artificially structured soil," *Eng. Comput.*, vol. 34, no. 1, pp. 175–186, 2018, doi: 10.1007/s00366-017-0528-8.

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